

# Crop Diseases Severity Identification by Deep Learning Approach

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**Abstract:** Improving yield and maintaining crop strength with optimization in use of resources are the major requirements in smart farming. To build a smart decision support system for improving production with flexibility, it requires Remote Sensing Systems. Now days with effective use of machine learning and deep learning techniques, it is possible to make the system flexible and cost effective. The deep learning based system has enormous potential, so that it can process a large number of input data and it can also control nonlinear functions. Here it should be discussed that from continuous monitoring of crop leaves images shall ensures the diseases identification. The research concludes that the quick advances in deep learning methodology will provide gainful and complete classification of crop with 98.7% to 99.9% accuracy. In this research, different crop diseases are classified based on image processing and Convolutional neural network method. For classification of maize crop diseases, different models have been developed, compared, and finally best one is found out. Also the finest model has been tested for different crop diseases to check its consistency.

**Keywords:** machine learning, deep learning, Probabilistic Neural Network, Convolutional neural network.

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## I. INTRODUCTION

In agriculture field, plant disease is the precarious and unavoidable trouble as it decreases the yield. Plant disease severity is a key measurable factor to determine infirmity stage and hence it can be used to guess yield along with advocate action. Maize crop leaves have lots of disease and the high level of damage. The quick, truthful verdict of illness extremity will assist to increase the production. Conventionally, botanist scientist and experts examined plant disease severity by continuous monitoring of plant tissue. This process is very costly and less effective. Manual assessment of plant crop diseases is obstructing the fast growth of modern agriculture [1]. Now days, the disease diagnosis for crop is become fully automatic with use of digital cameras and commuter vision by preparing smart deep neural network models with different techniques. So the aim of the research is to classify plant diseases fully automatic and quickly with flexible manner.

Maize is a significant food and most occupied crop. Its whole yield is the biggest in the globe apart from for rice and wheat [2]. First we developed a deep neural network model in favour of classifying maize crop leaves in different class by monitoring the images of leaves so that we can conclude that the crop is healthy or it has some disease. To

discover finest network architecture, initially we trained the general models with different depth from scratch and then we prepared high tech models by using pre-trained weight. The finest model achieved an accuracy of 98.7% of correct prediction for rest of test data set. Also the same model is used for different crop images to verify its performance. The comparison for different objects with same model is shown. Our results are better than previous work as mentioned in paper.

Part wise summary of the whole manuscript is given here. Part II indicates the related work in this field. Part III indicates the deep learning scheme. Part IV explains the tactic. Part V shows the algorithm for model preparation. Part VI shows result analysis for maize crop. Part VII shows the testing of same model with different dataset to check its consistency. Part VIII shows the results and associated discussions, and at last conclusion is presented.

## II. RELETED WORKS

So many researchers have found that, it can be possible to achieve improved accuracy and excellent results through the image based assessments approaches, as compare to manual assessments for crop disease identification. Xihai Zhang et al. prepared models using GoogLeNet and

Cifar10 for diseases classification for maize crop leaves and achieved high accuracy of 98.9% and 98.8% respectively. But in this case they utilized input from different source; also the no. of original image was 500 only. So they had to raise the dataset by several techniques [3]. K. Song et al. proposed a scheme by applying SVM for recognition for a range of diseases in maize crop leaves. The finest accuracy for detection is 89.6%. But this tactic is applied on small samples and the result degraded with increasing no. of samples [4]. L. Chen and L. Y. Wang projected a technique for the detection of diseases in maize leaves through image processing and PNN. The finest accuracy achieved by this is 90.4%. In this method if no. of training samples increases then detection accuracy and speed both are degraded [5]. Apart from this, various efforts had been taken for maize leaf disease [6, 7, and 8]. Stewart et al. used a computerized image inspection scheme to find diseases for spoiled wheat plants caused by *Zymoseptoria tritici* [9]. In this scheme the evaluation of pycnidia dimensions and thickness besides through many parameters and their correlation is enabled which provide high accuracy and precision compared with manually estimated accuracy. Guan Wang et al. developed algorithm based on deep neural network for apple crop in which from the images of leaves it can be possible to identify the health stage of crop with 90% accuracy [10]. J. G. A. Barbedo prepared an image segmentation scheme to figure out the level of disease for grey environment which overcome the human error [11]. Le Hoang Thai illustrated image recognition. The accuracy was good in this research, but the processing time efficiency needs to improve when it comes to complex image classification, such as facial image [12]. Y. Atoumet al. developed a scheme of computer vision method called Cercospora Leaf Spot (CLS) Rater, to exactly specify crop images in the existent situation. It achieved fine reliability than manual ratings [13]. S. Choi and S.T. Hang prepared a model for plant Identification. They won the first prize in plantCLEF2015 and plantCLEF2016 respectively [14, 15]. M. Mehdipour Ghazi, pooled the output from both GoogleNet and VGGNet and increase validation accuracy [16]. S. Sladojevic formed a dataset through internet and prepared a model to classify 13 dissimilar types of plant diseases [17]. S. P. Mohanty, prepared a neural network model for identifying 14 crop species and 26 diseases for more than 54000 images of public dataset Plant Village [18, 19]. Almost all these image-based evaluation techniques for plant diseases exhibit the similar fundamental process [20-23]. Determining an effective classification method, assortment of training samples, extraction of image processing features, collection of appropriate classification approaches, post-

classification processing, and accuracy assessment may be the most critical stage in image classification [24-26]. Classification of images with different machine learning techniques will enable us to retrieve the many important parameters. One of the biggest rewards of machine learning and deep learning approaches is that they can use datasets from different sources to solve complex non-linear problems independently. Machine learning and deep learning techniques offer data-driven administrative analysis. They also provide the introduction of intelligence into the system with a strong and versatile structure [27, 28]. The excellent performance of machine learning and deep learning methods, make them extensively applicable to precision agriculture. In particular, knowledge of change in plant fitness, physiology, and nutrient status can permit for the application of different treatments or treatment severity to exact crop area. The functional recognition and isolation of areas is usually done with separating a wide farm area into smaller control segments with defined separate treatments. The deep learning techniques are also used for speech analysis, exposure of an object, and several other areas such as robotics, medical-field, etc. [29].

### III. PROPOSED METHODOLOGY

#### A. *Scratch Learning*

In proposed scheme the comparison of different models is carried out for maize crop leaves. First from the scratch images we build simple convolutional architecture and then we go for transfer learning in which the concept of hyper parameter tuning is applied at the top layers of pretrained model. Here we use adequate amount of training data to find best classification for diseases severity. The simple architecture model consists of few convolutional layers each has one or more filters, followed by fully connected layers. Here we apply softmax normalization after train simple models of 1, 3, 5...13 convolutional layers. Each convolution layer has 32 filters with 3 X 3 Rectified Linear Units activation (ReLU). Now every layer is followed by 2 X 2 max pooling layer. The no. of filters for max pooling layer is 64. The entire initial fully connected layer has 64 units, each has ReLU activation. The dropout layer with 50% ratio is just after initial layers. The final fully connected layer has 4 outputs, related to the 4 classes. This output data is applied at softmax layer to estimate the final output probability. After finding the best model we test this model for other dataset like apple, grape and tomato to evaluate its performance.

#### B. *Concept of Transfer Learning*

Transfer learning is a valuable technique to construct dominant classification network

pretrained on large no. of entities, like ImageNet. Here the diseases severity classification is more important and it is embattled for best image categorization task compared to the ImageNet, the lower layers are responsible to encode only initial features. For transfer learning we compare VGG16, VGG19, MobileNet2, Xception, ResNet152v2 architectures [3, 10,29]. Amongst all Resnet152v2 give highest accuracy and placed at first position. The VGGNet has 16 (VGG16) and 19 (VGG19) weight layers and gives an important expansion on previous configurations with an architecture through incredibly small convolution filters. MobileNet uses batch wise and ReLU activation technique. It first goes for depth wise separable convolutions then for width multiplier and at last it does resolution multiplier. Mobile Net has extremely small processing power for executing transfer learning .Due to this it become ideal in support of handheld devices, embedded systems and computers without a GPU or poor computing power, with the precision of the results being drastically compromised. The Xception model has 36 convolutional layers. The 36 convolutional layers are structured into 14 sets. Apart from first and last set every set has linear residual connections around them. ResNet exhibits a *configuration* called residual learning unit to improve the performance of deep neural networks. Here all this are combined with transfer learning to achieve desired output.

IV. EXPERIMENTAL SETTINGS

A. Material Analysis

The new plant diseases image dataset is a public dataset, anyone can utilize it. It has 38 directories with different class names and approximately 60000 images of healthy and diseased crops. First we select the maize crop leaves images as an input datasets. The leaves images are classified in Healthy class, Leaf Spot class (Brown spot, Round Spot, curvularia spot, grey leaf and Dwarf mosaic), Leaf Blight class (Northern and southern) and Rusty class . Each image is belongs to particular class. The leaves belongs to Healthy class leaves have no spot and they have structure shown in figure 1(A). The Leaf Spot leaves have one circular spot approximately with radius 2.5mm as shown in figure 1(B).The Leaf Blight class leaves have more no. of spots and may be they are merged together to form a larger mass of diseased tissue as shown in figure 1(C). Rust class leaves are shown in figure 1(D). They are fully diseased and they can be dropped from tree. In this work total 9145 images of different types of maize leaves are taken in to account for developing algorithm for classification. Here 7316 images are given for training the algorithm and remaining 1829 images for evaluate the algorithm. For testing the algorithm we split the

train images in to two parts. 80% of images are used to developing a model and remaining 20% images are for testing the model.

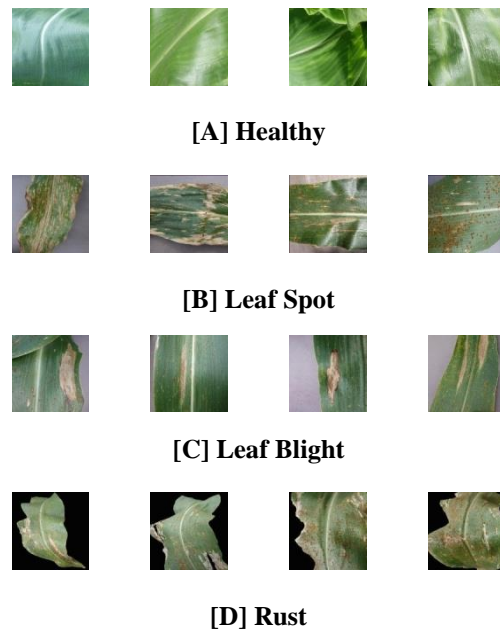


Fig. 1. Original Maize Crop Leaves Images

Table I shows the bifurcations of different types of class and relative no. of images. Here the no. of samples for each class should be fair to diminish the bias. Our policy of balancing is as follows: for each type of class we select 80% of images as train dataset and 20% of images as test dataset. Validation images are separately given in dataset. Here we do not go for any type of clustering as it increases approximation loss.

- No. of samples for Train Dataset – 5851
- No. of samples for Validation Dataset- 1829
- No. of samples for Test Dataset-1465

TABLE I. NO. OF SAMPLES FOR TRAINING, VALIDATION AND TEST DATA SETS

Class	No. of images for Training	No. of images for Validation	No. of images for Test
Healthy	1487	465	372
Leaf Spot	1313	410	329
Leaf Blight	1526	477	382
Rust	1525	477	382
Total No. of images	5851	1829	1465

B. Model preparation

The samples of the new plant diseases datasets are 256 X 256 sized RGB images. First a generalize model from the scratch images for diseases prediction is developed. At this point we donot use any pretrained weight. In the next step we convert images in to size of 224 X 224 for VGG16, VGG19, MobileNetv2, Xception and ResNet152v2. Here we execute the optimization and prediction of model for these images. Because of, compatibility with the different architecture; it must be require that the value of all pixels is divided by 255. After all this, the normalization is carried out to improve end to end training. For this every input  $i$ , we determine the mean value  $m_i$  and standard deviation  $s_i$ . After it we transform the input to  $i' = (i - m_i) / s_i$ . It should be observed that, particular for this dataset, any kind of augmentations degrades the performance of models, so it should be ignored.

*C. Convolutional Neural-Network approach*

The architecture of CNN starts with numerous Convolutional and pooling layers. Fully connected layers are placed just after them. For any input  $i$  from  $j^{th}$  Convolutional layer, it calculates,

$$I_{jc} = \text{ReLU}(Y_j * i) \dots \dots \dots (1)$$

Here  $*$  depicts the convolution function and  $Y_j$  shows the convolution kernels of the layer.  $Y_j = [Y_j^1, Y_j^2, \dots, Y_j^w]$ . Here  $w$  represents the no. of convolution kernels of the layer. All kernels  $Y_j^w$  are  $m \times m \times n$  weight matrix with  $m$  is the window size and  $n$  is the no. of channels.  $\text{ReLU}(i) = \max(0, i)$  is rectified linear unit. It is applicable as an activation function for these models.  $\text{ReLU}$  trains a number of times quicker than saturated nonlinear function like Sigmoid. The max-pooling layer calculates the highest value over non overlapping rectangular regions of the outputs for all convolution kernels. The pooling function enables position invariance over larger local regions and reduces the size of output. On the top of final convolution layers, the fully connected layers are embedded. Here fully connected layers computes  $\text{ReLU}(Y_{fc}i)$ , where  $i$  is the input and  $Y_{fc}$  is the weight matrix for the fully connected layer. To measure the difference between predicted outcome and the class-name of the input, the loss function is used. The loss function is just the addition of cross entropy,

$$E(Y) = \frac{-1}{n} \sum_{ij=1}^n \sum_{w=1}^w [y_{jw} \log P(i_j=w) + (1 - y_{jw}) \log (1 - (i_j=w))] \dots \dots \dots (2)$$

Here  $Y$  shows the weighting matrixes of convolutional and fully connected layers. Here no. of training sample is represented by  $n$ .  $j$  and  $w$  is order no. of training samples and classes respectively.  $y_{jw} = 1$  if the  $j^{th}$  no. of sample is from

$w^{th}$  no. of class. Otherwise  $y_{jw}=0$ .  $P(i_j=w)$  is the probability of input  $i_j$  belonging to the  $w^{th}$  class that the model predicts, which is a function of parameters  $Y$ . Here loss function takes  $Y$  as its parameters. The goal of network training process is to find the value of  $Y$  that minimizes the output of loss function  $E$ .

*D. ADAM optimizer*

Adaptive Moment Estimation (Adam) is technique that enumerates adaptive learning rates for all parameters. It stores an exponentially decaying average of past squared gradients  $y_t$ , as well as it also keeps an exponentially decaying average of past gradients  $x_t$ . We calculate the decaying averages of past and past squared gradients  $x_t$  and  $y_t$  respectively as given below.

$$x_t = \beta_1 x_{t-1} + (1 - \beta_1) g_t$$

$$y_t = \beta_2 y_{t-1} + (1 - \beta_2) g_t^2$$

Here  $x_t$  and  $y_t$  are estimation of the first moment (mean) and the second moment (variance) of the gradients respectively. Also both  $x_t$  and  $y_t$  are biased towards zero, particularly at preliminary time steps and also when decay rate is small. These biases can be neutralized by computing bias-correction and second moment. With use of  $x'_t$  and  $y'_t$ , it can be easily revise other parameters.

$$x'_t = \frac{x_t}{1 - \beta_1^t}$$

$$y'_t = \frac{y_t}{1 - \beta_2^t}$$

Here the learning rate of 0.001 is used for better performance. The learning rate is significant parameter as it is responsible for step size of learning. We employ early stopping similar to close policy to discontinue training when the network starts to over fitting. After each epoch we evaluate the performance of the network using the validation loss. When the loss value regarding the validation data stopped getting better, the network will discontinue training.

Now Transfer learning is executed in such a way so that the difficulty of over-fitting is overcome. During training, all convolution layers used the same weights present in the all network architecture and top layers are not included from architecture We have replaced top layers with only one fully connected layer which resembles the number of categories available in the training dataset. With this approach, we are fine-tuning fully connected layers to train a mode based on our custom training dataset.



V. ALGORITHM

Input: New Plant Village Dataset.

Output: Classification of different crop diseases.

- Step 1: Get the ‘New Plant Village’ Dataset from ‘kaggle’ machine learning repository.
- Step 2: Split the dataset in to the ratio of 80% / 20% for training and testing.
- Step 3: The pre-processing of data is done for rescaling of images, batch size etc.
- Step 4: Select different base model like VGG16, VGG 19, MobileNetv2, Xception, ResNet152V2 etc.
- Step 5: Initially ‘base\_model.trainable = False’ and apply transfer learning as mention below.
  - First add ‘GlobalAveragePooling2D()(x)’ layer so the network requires small amount of parameters to learn.
  - Next we add ‘Dropout’ layer to overcome the problem of over-fitting.
  - At last ‘Dense’ layer is applied to get appropriate output.
- Step 6: Select ADAM optimizer, epoch =100 and early stopping by monitoring validation loss with patience =5.
- Step 7: Train the model and find the accuracy.
- Step 8: Now test the model with test dataset.
- Step 9: Now apply the concept of hyper parameter tuning, by repeating all the steps from step no.5 except ‘base\_model.trainable = True’.
- Step 10: Find the accuracy and confusion matrix.

VI. OUTCOME ANALYSIS FOR MAIZE CROP DATASET.

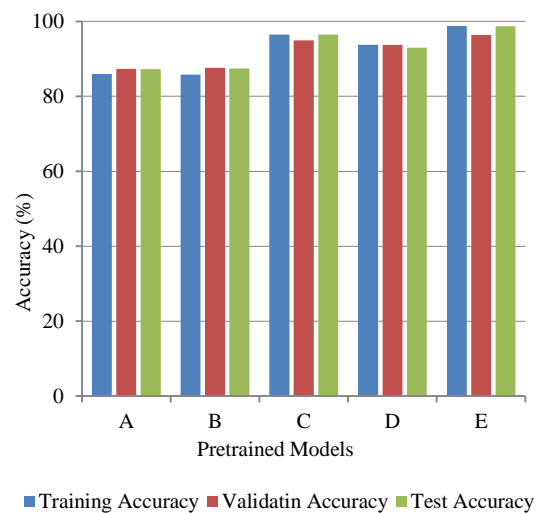
Initially the model was prepared from the scratch images, and pretrained weight is not applied. Here we see that if we are going to increase the convolution layer, both training and test accuracy is going to increase. But after certain limit if we add layers, both these accuracies are decreases due to inadequate training data for models with more no. of parameters. The highest test accuracy that we achieved is 78.5% with 9 convolution layers. To avoid this trouble, transfer learning is applied to the

modern deep models. After applying transfer learning, we freeze the layers of model and get training accuracy 98.78%, validation accuracy 96.44% and test accuracy is 97.13%. To improve test accuracy further, the concept of hyper parameter tuning is utilized.

TABLE II. THE HYPER PARAMETER OF TUNING

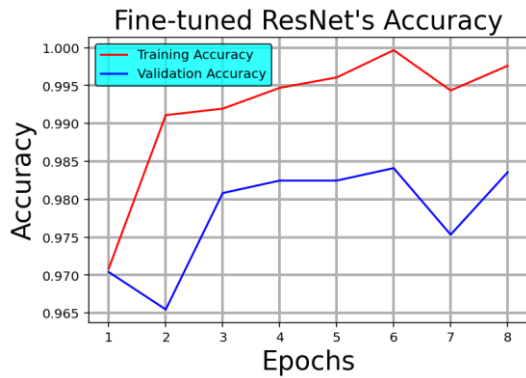
Class	No. of images for Training	No. of images for Validation	No. of images for Test
Healthy	1487	465	372
Leaf Spot	1313	410	329
Leaf Blight	1526	477	382
Rust	1525	477	382
Total No. of images	5851	1829	1465

The results after hyper parameter tuning for the ImageNet pretrained models are shown in Figure 4. Every column depicts the average outcome for 20 epochs. The final accuracy on the test set is varies from 87.26% to 98.7%. The output from fine-tuned models is greater to that of models trained from scratch. The most excellent result is obtained with ResNet152v2 model, which has an accuracy of 98.7%. The results specify that transfer learning overcome the difficulty of inadequate training information. For evaluation, we prepared one ANN model is trained by Adadelta optimizer along with training data samples. We get test accuracy only 36%, which is like accidental prediction.



[A] VGG16 [B] VGG19 [C]Xception  
[D] MobileNetv2 [E] ResNet152v2

Fig. 2. Accuracies of different Deep Model



(A)



(B)

Fig. 3. (A) Accuracy and Loss of ResNet152v2 after Hyper Parameter Tuning

The convolutional feature extractor is required for the ANN to pull out basic correlations along with searching the particular features from the images. The figure 3(A) and 3(B) shows the graphs of accuracy and loss for training and validation without hyper parameter tuning and with hyper parameter tuning. The confusion matrix of the ResNet152v2 model on the present test set is given in Table 3. The part of accurately predicted images for all of the four classes is shown.

TABLE III. CONFUSION MATRIX FOR THE PREDICTION OF RESNET152V2 MODEL TRAINED WITH TRANSFER LEARNING FOR MAIZE CROP.

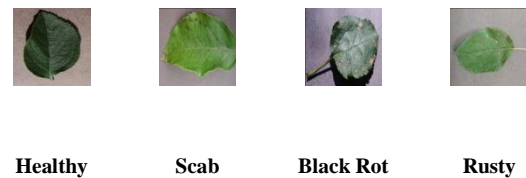
		Predicted Result			
		Healthy	Leaf blight	Leaf spot	Rusty
Actual Class	Healthy	368	0	0	0
	Leaf blight	0	368	10	0
	Leaf spot	0	8	324	0
	Rusty	0	0	0	382

All the leaves for Healthy- class and Rusty-class are correctly classified with 100% accuracy. The accuracy of Leaf- spot class is 97.59%. Only 8images out of 329 are predicted wrong. The

accuracy of Leaf blight images is 97.35%. Only 10images out of 368 are predicted wrong. Total 1446 images out of 1465 predicted correctly. All the parameters of model like precision, recall, and f1 score is 0.99. Here, the mistyped classes are merely mystified with their nearby class. For the case, leaf blight class and leaf spot class are confused with each other.

### VII. MODEL CONSISTENCY

This model is also test on different plant dataset to evaluate its reliability. We take Apple, Grapes and tomato images and test the model. We got better performance as compare to maize dataset. The apple leaves images are classified in Healthy class, Black Rot class, Scab class and Rusty class. The apple Scab and apple black rot disease are due to fungus. The grape leaves are classified in to Healthy class, Leaf Blight class, Black Rot Class and Esca (Black\_Meases) Class. Like apple, in grapes also the fungus creates two diseases Black Rot and Esca (Black\_Meases). The tomato dataset is very large with more no. of classes. Total 10 types of diseases are integrated including healthy images. It includes the diseases due to fungus or unbalanced weather. These are Bacterial Spot, Early Blight, Late Blight, Leaf Mold, Leaf Spot, Spider Mite, Target Spot, yellow Leaf Curl Virus, Mosaic Virus. Figure 4(a), 4(b) & 4(c) shows each class sample for visualization of diseases for different crop.



(A) Apple Crop Leaves Images



(B) Grapes Crop Leaves Images



Healthy Bacterial Spot Early Blight Late Blight Leaf Mold

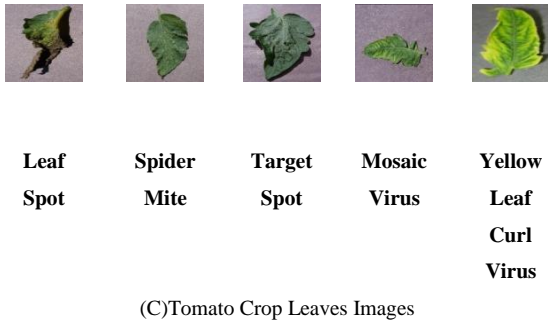


Fig. 4(A) 4(B) & 4(C) Original Leaves Images for Different Crops Diseases

Table 4(A), 4(B) & 4(C) show the bifurcations of different types of crop-class and relative no. of images. Also we take enough no. of samples for each class to diminish the bias. The same policy for training, validation and test is executed as we have performed for maize crop.

**Apple:**

- No. of samples for Train Dataset – 6220
- No. of samples for Validation Dataset-1943
- No. of samples for Test Dataset-1557

**Grapes:**

- No. of samples for Train Dataset – 5783
- No. of samples for Validation Dataset-1815
- No. of samples for Test Dataset-1448

**Tomato:**

- No. of samples for Train Dataset – 14686
- No. of samples for Validation Dataset-4585
- No. of samples for Test Dataset-3678

TABLE IV (A). NO. OF SAMPLES- FOR TRAINING, VALIDATION AND TEST DATA SET FOR APPLE CROP.

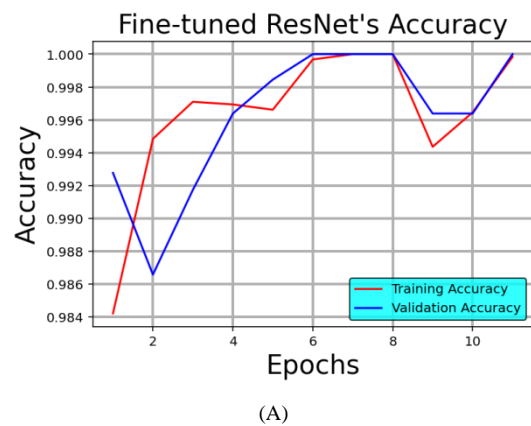
Class	No. of images for Training	No. of images for Validation	No. of images for Test
Rusty	1408	502	352
Scab	1612	497	404
Healthy	1611	504	403
Black Rot	1589	440	398
Total No. of images	6220	1943	1557

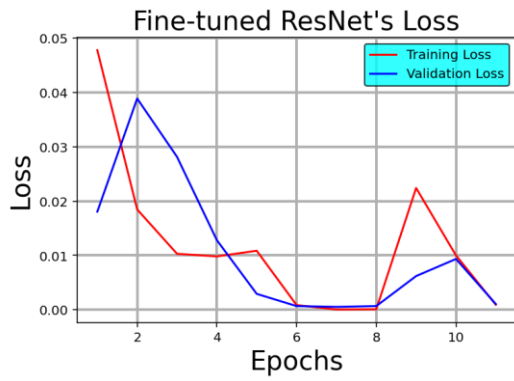
TABLE IV (B). NO. OF SAMPLES- FOR TRAINING, VALIDATION AND TEST DATA SET FOR GRAPE CROP.

Class	No. of images for Training	No. of images for Validation	No. of images for Test
Leaf Blight	1377	430	345
Healthy	1353	423	339
Esca(Black Measles)	1536	490	384
Black Rot	1517	472	380
Total No. of images	5783	1815	1448

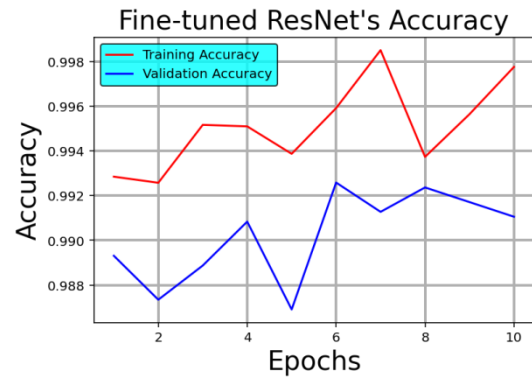
TABLE IV (C). NO. OF SAMPLES- FOR TRAINING, VALIDATION AND TEST DATA SET FOR TOMATO CROP.

Class	No. of images for Training	No. of images for Validation	No. of images for Test
Bacterial Spot	1368	470	343
Early Blight	1536	448	384
Mosaic Virus	1440	463	360
Late Blight	1480	457	371
Target Spot	1461	425	366
Spider-mites Two-Spotted – Spider Mite	1392	490	349
Leaf Mold	1505	436	377
Yellow Leaf Curl Virus	1568	480	393
SeptoriaLeaf Spot	1396	481	349
Healthy	1540	435	386
Total No. of images	14686	4585	3678



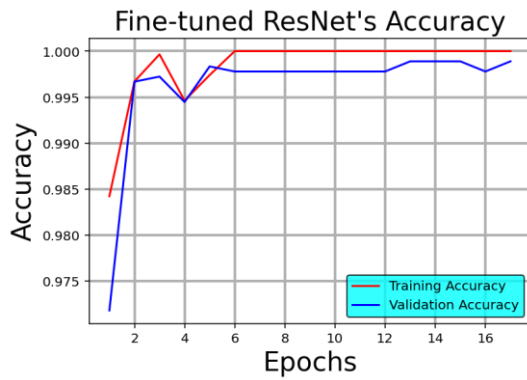


(B)

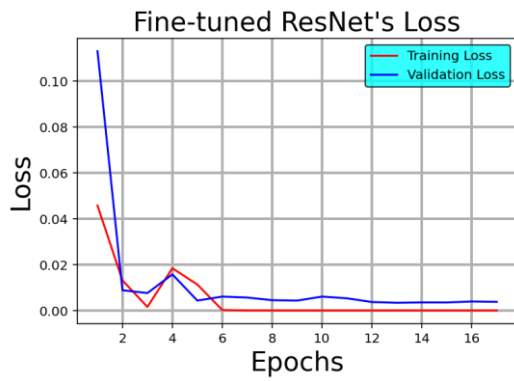


(A)

Fig. 5(A) and 5(B) Accuracy and Loss of ResNet152v2 after Hyper Parameter Tuning - Apple Crop

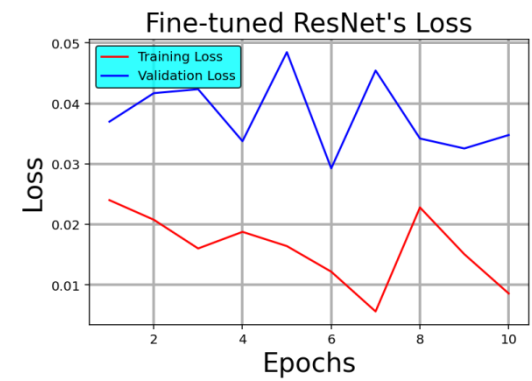


(A)



(B)

Fig. 6(A) and 6(B) Accuracy and Loss of ResNet152v2 after Hyper Parameter Tuning – Grape Crop



(B)

Fig. 7(A) and 7(B) Accuracy and Loss of ResNet152v2 after Hyper Parameter Tuning – Tomato Crop

TABLE V(A). CONFUSION MATRIX FOR THE PREDICTION OF RESNET152V2 MODEL TRAINED WITH TRANSFER LEARNING FOR APPLE CROP.

		Predicted Result			
		Scab	Black Rot	Rusty	Healthy
Actual Class	Scab	404	0	0	0
	Black Rot	0	398	0	0
	Rusty	0	0	351	1
	Healthy	0	0	0	403

TABLE V(B). CONFUSION MATRIX FOR THE PREDICTION OF RESNET152V2 MODEL TRAINED WITH TRANSFER LEARNING FOR GRAPE CROP.

		Predicted Result			
		Black Rot	Esca(Black Measles)	Leaf Blight	Healthy
Actual Class	Black Rot	380	0	0	0
	Esca(Black Measles)	2	382	14	0
	Leaf Blight	0	5	345	0
	Healthy	0	0	0	339



Table V(C). Confusion Matrix for the prediction of ResNet152v2 model trained with transfer learning for tomato crop.

		Predicted Result									
		Bacterial Spot	Early Blight	Late Blight	Leaf Mold	Leaf Spot	Spotted Spider Mite	Target Spot	Yellow Leaf Curl Virus	Mosaic Virus	Healthy
Actual Class	Bacterial Spot	342	0	0	0	0	0	1	0	0	0
	Early Blight	0	380	2	0	0	1	1	0	0	0
	Late Blight	0	1	368	0	2	0	0	0	0	0
	Leaf Mold	0	0	0	376	0	0	0	1	0	0
	Leaf Spot	2	0	0	1	346	0	0	0	0	0
	Spotted Spider Mite	0	1	0	0	0	346	2	0	0	0
	Target Spot	2	0	0	0	0	0	363	0	0	1
	Yellow Leaf Curl Virus	0	0	0	1	0	0	0	392	0	0
	Mosaic Virus	0	0	0	0	0	0	0	0	360	0
	Healthy	0	0	0	0	0	0	0	0	0	386

From the graphical analysis and confusion matrix it is quite acceptable that the accuracy of model closer to 100% when the early stopping is triggered. Deep learning is data-driven and hence if we apply more data for training the test accuracy is increase more and more. Here we remember that ResNet152v2 model performed most excellent among all. As shown in the result is far better than of [15, 16], where the VGGNet gave performance in the PlantCLEF plant identification task.

VIII. RESULTS AND DISCUSSIONS

Here in this research we emphasized on end to end solution for diagnosing plant diseases severity. We develop a deep neural network model which trained with few training samples with different depth from scratch and fine-tuned five modern deep models: VGG16, VGG19, Xception, MobileNetv2 and ResNet152v2. In contrast to test accuracy we found that hyper parameter tuning is very significant to get better the performance of deep models.

Table 6 shows the significant parameter for all datasets. The test accuracy is nearly about 100% for apple, grape and tomato. The precision, recall and F1 score is 1.00 for Apple crop while for grape and maize, it is 0.99. For tomato dataset these values are little bit less around 0.92, because there are lots of close, similar nearby class.

TABLE VI. MODEL PARAMETERS FOR DIFFERENT OBJECTS

Crop Image	Maize	Apple	Grapes	Tomato
Model	ResNet152v2			
No. of Original Images	9145	9720	9046	22949
Optimizer	ADAM			
Test Accuracy	98.7%	99.93%	99.86%	99.48%
Loss	0.0523	0.0013	0.0024	0.0153
Precision	0.99	1.00	0.99	0.92
Recall	0.99	1.00	0.99	0.92
F1 Score	0.99	1.00	0.99	0.92

TABLE VII. COMPARISON WITH PRIOR WORK

Crop Image	Ref. [3]	Ref. [10]	Proposed work			
	Maize	Apple	Maize	Apple	Grape	Tomato
Model	Goog LeNet	VGG 16	ResNet152v2			
No. of Original Images	500	1674	9145	9720	9046	22949
Optimizer	SGD	SGD	ADAM			
Test Accuracy in (%)	98.9	90.4	98.7	99.93	99.86	99.48

The fine-tuned ResNet152v2 model performs the best and achieved an enormous accuracy of 98.7% to 99.93% on the test set. And it is quite better than reference no. [10]. Table 7 shows the comparison of proposed work with previous research. The average accuracy for other techniques is 94.71% [3]. While we compare our work with reference [3] we observe that the accuracy is almost same, but it is fairly shown that we have work on 9165 images which is to much higher than 500 image dataset used in reference [3]. Also, they not only collect images from different source, but to overcome over-fitting during training, they go for expansion of dataset which is somehow not reliable. The model gives better performance on apple, grapes and tomato image dataset. The equipped model exhibits enormous potential on classification for different dataset also. For apple crop dataset we achieved 99.93% accuracy which is absolutely great. The healthy class, apple-scab class and apple black-rot class identified with 100% accuracy. Only one image of rusty class recognized as healthy class. The result is far better than reference [10]. For grape dataset we also got accuracy about 99.86%. The black-rot class, leaf blight class, and healthy class identified with 100% accuracy. Only two image of Esca class recognized as black-rot image because of close similarities. The tomato dataset is versatile with more no. of diseases class. For tomato dataset we achieved 99.48%. The loss value is quite low say 0.0013 and 0.0024 for apple and grape. For tomato the loss value is 0.0153 it merely low as compare to maize in which the loss value is 0.0523.

#### Conclusions

A Scheme is proposed for deep learning approach to find out the selective features for different diseases severity classification without human intervention. The whole research indicates that the deep learning shows potential for diseases recognition in crop. The proportion of training and testing is 80% and 20%, respectively. The diseases detection technique used in proposed work permit the systems to attain a variety of sample images. The process of pooling, activation (ReLU) and dropout enhance the ability of system. In further study, we will discover more types of crop diseases. Also we will combine innovative techniques and other deep learning algorithms for the better performance. To facilitate agriculture productivity with fast classification, the model can easily built with mobile devices.

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